Deep Learning for Model-Free Prediction of Thermal States of Robot Joint Motors

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Abstract: In this work, deep neural networks made up of multiple hidden Long Short-Term Memory (LSTM) and Feedforward layers are trained to predict the thermal behavior of the joint motors of robot manipulators. A model-free approach is adopted. It allows for the accommodation of complexity and uncertainty challenges that might compromise the derivation, identification, and validation of a large number of parameters of an approximation model that is hardly available. To this end, sensed joint torques are collected and processed to foresee the thermal behavior of joint motors. Promising prediction results of the machine learning based capture of the temperature dynamics of joint motors of a redundant robot with seven joints are presented.

Keywords: Robotics, Thermal Management, Artificial Intelligence / Machine Learning.

1. INTRODUCTION

Robots are commonly used to unrelentingly achieve repetitive and hazardous tasks in industry and society. Meanwhile, they increasingly and skillfully assist and augment humans. Included are dynamic applications with a pronounced level of physical interactions between humans and robots, such as using a robot as a companion (Basha (2025)), home-helper and caregiver (Tsui et al. (2025),Gkiolnta et al. (2025)), as well as a prosthesis (Kim et al. (2025)). In this respect, large joint accelerations, high payload manipulations, and motions with specific configurations (see, e.g., Fig. 1) can induce an overheating of joint motors of robots. An excessive motor temperature can accelerate the degradation of insulation materials and reduce the motor efficiency (Yehorov et al. (2025)) along with jeopardizing the positioning accuracy of the robot because of axial deformations and drifts (Soga et al. (2024)).

Most robot manufacturers, including Franka, Kinova, and KUKA, offer built-in functions to shut down the robot once a critical temperature threshold is attained. Whereas this functionality is advantageous to preserve the performance and reliability of motors and surrounding electronic components, an undesired shutdown is likely to compromise the robot availability for production and assistance purposes. This situation gets exacerbated as the robot is not equipped with mechanical breaks as in Fig. 1. In this case, critical collisions with the environment might occur, endangering human beings or leading to hardware (i.e., robot, workpiece, workcell, etc) damages. Furthermore, thermal burns represent not only a severe safety issue in physical human-robot-interaction but also a hindrance for elevated user experience that is necessary to engage and sustain a symbiosis between humans and robots.

Predicting the thermal behavior of robot joints is an essential step toward the development of countermeasures that help anticipate overheating, preserve the robot availability, prolong its lifetime, and improve its usability. The Industry 4.0, Industry 5.0, Society 5.0, and Society 6.0 realms are likely to benefit from this capability. This is because it propels operational efficiency through intelligent thermal management of the robot for availability purposes. It also supports decent and sustainable haptic working conditions for the workforce, as well as human-centered robotized servicing for comfortable smart living and social well-being in different ecosystems. Meeting such goals requires an approach that can turn robot diversity and application uncertainties into competitive advantages in terms of flexibility, insights, transferability, and scalability.

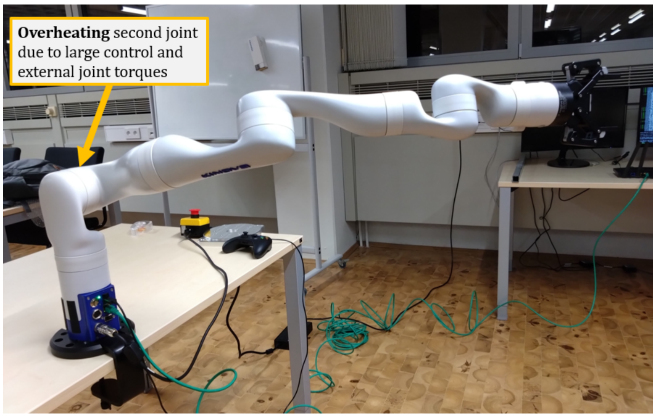

Fig. 1. Robot posture increasing a motor temperature.

This work predicts the thermal behavior of joint motors of robots with the following key contributions. The prediction approach is

- data-driven, paving the ground for an insightful, non-invasive, and inclusive operationalization in real-time. The approach therefore follows design objectives of

our overarching Metarobotics framework (Kaigom (2023)). In our previous work (Abt et al. (2025)), the thermal behavior of robots is sensed and virtually made accessible to even novices through immersive, dynamic, and intuitive monitoring and control driven by digital twins (Kaigom and Roßmann (2020)). Since most robots do not output temperature data, we extend our previous work by capturing their thermal motor behavior from observed actuation profiles.
- model-free through the development of a deep learning based framework that leverages multiple hybrid layers to learn the underlying thermal dynamics of joints from sensed data commonly available via application programming interfaces (APIs). It is worth noting that no system-related parametric or actuation profile assumptions are made. These particularities are useful to avoid model complexity while fostering generalization and transferability to other robot types regardless of the number and type of joint motors.
- evaluated on data collected from a redundant robot with seven joints.

2. RELATED WORKS

Predicting the temperature behavior of robot motors has attracted attention in the recent years. Online learning of thermal model parameters of a such motor is carried out in Kawaharazuka et al. (2020). The goal is a precise forecasting of the motor core temperature of musculoskeletal humanoid robots. An enhanced model allows to predict maximum output motor torques. Anomalous behaviors are detected by analyzing variations of thermal dynamics. Thermal control is developed to limit the tensions in the actuation of the musculoskeletal humanoid. In order to safely operate a motor at torques which are considerably larger than its rated torques, Singh et al. (2021) capture and regulate core temperatures via current control. To this end, a thermal abstraction model is developed and employed to design the thermal controller. The goal is to keep the stator temperature below a heating threshold while avoiding risks of high torques. A method is proposed to control the maximum limit of the current to this end. A forced cooling approach is applied to influence the thermal resistance, steady-state current, and output torque. However, cooling strategies might be challenging to implement once the robot is in use potentially in toughly accessible environments (e.g., space orbits). In this case, intelligent thermal management approaches are helpful.

Afaq et al. (2023) focus on thermal management of robotic applications under extreme temperatures. Electronics heating and cooling are considered. A temperature control driven by fuzzy logic is developed and demonstrated to this end. Decreases of extreme high temperature from 50° to 8° are shown. Fan-based forced convection is used to cool electronics. Excessive internal temperatures in a permanent magnet synchronous motor (PMSM) taking non-stationary loads, which might lead to a reduction of its life time, is addressed in Chen et al. (2024). An accelerated degradation model is derived to evaluate the reliability function and predict the lifetime of the PMSM under thermal stress. Geometric backlash and temperature-related drift errors in joints of industrial robots are compensated in Sigron et al. (2023). A model that reflects the thermal expansion of links is developed and used for thermal expansion correction. LSTM Neural Networks (He et al. (2024)) and Pseudo-Siamese Nested LSTM (Cai et al. (2021)) are employed to predict the temperature in Permanent Magnet Synchronous Motors. A trapezoidal torque profile is employed in He et al. (2024) whereas the torque dynamics is not released in (Cai et al. (2021)). A thermal recovery of robot joints is achieved in Jorgensen et al. (2019). To this end, the thermal dynamics is captured as a first order ordinary differential equation subject to constant positive and negative step-like profiles of joint torques. The exponential-based dynamics of the temperature behavior is derived. A parameter identification is carried out to demonstrate the performance of the model for step-like joint torques. Another model-based approach is proposed in Trinh et al. (2023) to predict temperature-dependent joint frictions in industrial robots.

Contributions mentioned thus far are mostly model-driven. They fit with specific robots provided that parameters have been identified in advance. However, parameter identification requires noise robustness and low sensitivity (Zhang et al. (2024), de Hoyos Fernández de Córdova et al. (2024)), which might be a time consuming analysis task prone to additional uncertainties due to unseen/unmodeled/truncated dynamics (Shang et al. (2024)). Sometimes, such a process must be repeated from scratch for a given new robot, which inhibits quick and large scale automation involving multiple robots in terms of complexity, workload, and costs. As the robot is hardly accessible, such as in space servicing, identification tasks might be hard to complete because of limited access to pertinent (e.g., excitation) data. Autonomous task completion without human interventions, as expected by Industry 6.0, calls for machine learning-embedded solutions (Carayannis et al. (2024)) that can extend the robot intelligence for self-condition monitoring. The approach proposed in this work also falls into this category. Robot datasets available from standard APIs are harnessed to predict the thermal behavior of its joint motors. Trained machine learning models can be executed by dedicated services of digital twins with the physical robot is embedded to detect, communicate to other entities, and anticipate detrimental thermal issues. In contrast to related works, no restriction is made on robot types, number of joints, and actuation profiles.

3. DATA-DRIVEN PREDICTION OF THERMAL JOINT STATES

4. IMPLEMENTATION AND METHODOLOGY

[The following section describes the data management, the temperature curve approximation, for evaluation purposes with the neural network models and [the data preprocessing for the trainings] the training results?]

4.1 Data collection

The data from a Kinova Gen3 7 degrees-of-freedom ultra-lightweight robotic arm [kinova], has been recorded using a specially developed OPC Unified Architecture server (Girke et al. (2024)). Positions, temperatures, torques, velocities and currents of each of the seven joints are stored, via a client application, as parameters in CSV

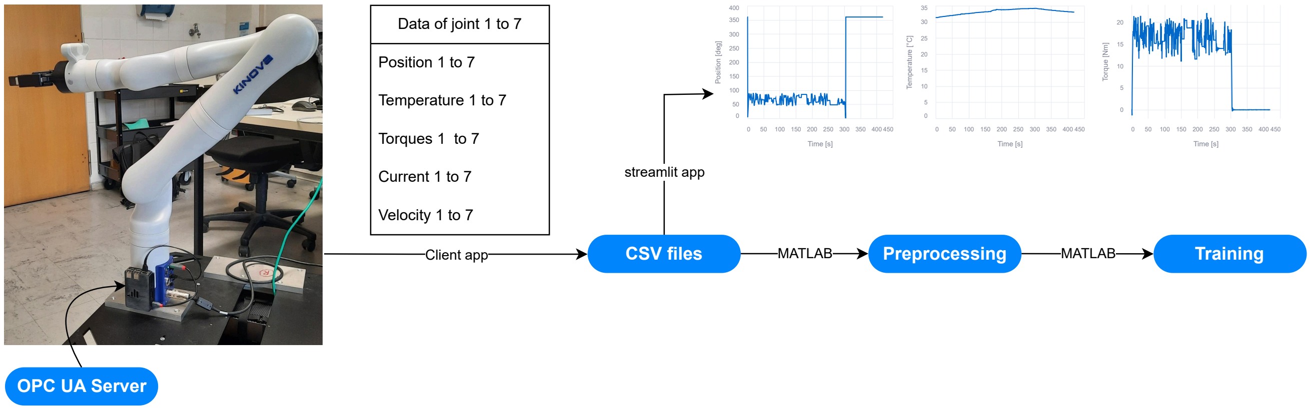

Fig. 2. Kinova data collection via OPC UA Server

files and subsequently processed for the neural network trainings, see Fig. 2. To cover a wide range of robotic movements, both randomly generated joint angle trajectories and predefined Cartesian trajectories for pick and place tasks, for example, were generated using the Kortex API (Robotics (2025)). The trajectories were initially performed at varying speeds and with different payloads. The recording duration of each set of trajectories was also varied in order to analyze the temperature rise and the cooling behaviour of the joints. For cooling, the robot was positioned in a vertical position, as this joint configuration imposes minimal load on the joints. However, the vertical position was not always used for cooling. To simulate real conditions, movements without intentional cooling were also conducted sequentially. To prevent collisions due to randomly generated joint angles, the random angular values were constrained within minimum and maximum limits. The result of this experiment indicate that joint 2 and joint 4 experience the most temperature increase and cooling. The data is freely available on our streamlit web app, which automatically visualizes the CSV files and displays the specific joint data. [1] For this reason, the focus was first placed on the 4th joint, while all other joints were fixed at 0°. Only the 4th joint was actuated with randomly generated values between two varying minimum and maximum angle limits (for example -90° and +90°).

4.2 Temperature curve approximation

(Parts of) The temperature curve can be represented approximately with the Gaussian model (i.e. Gauss2) as shown in Fig. 3 and (1):

$$\begin{aligned} f(x) = a_1 \cdot \exp\left(-\left(\frac{x-b_1}{c_1}\right)^2\right) \\ +a_2 \cdot \exp\left(-\left(\frac{x-b_2}{c_2}\right)^2\right) \end{aligned} \tag{1}$$

With the coefficients for Fig. 3:

$$a_1 = 34.07, \quad b_1 = 276$$
$$c_1 = 743.2, \quad a_2 = 1.668$$
$$b_2 = -26.71, \quad c_2 = 103$$

[1] https://irolabkinova.streamlit.app

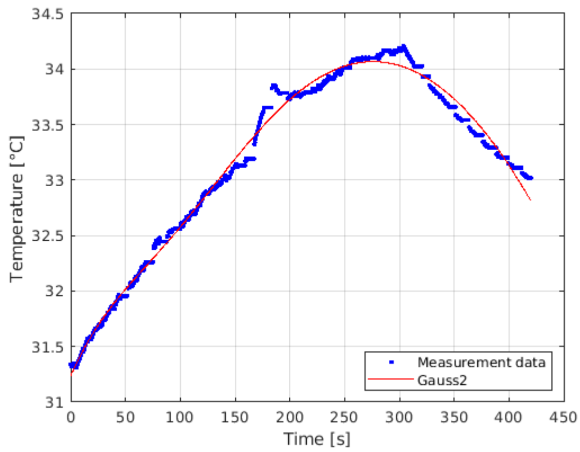

Fig. 3. Approximation of the temperature curve of the 4th joint with the Gauss2 function

[Sum of Squared Errors (SSE): 5.4852
Mean Squared Error (MSE): 0.0066087]
Root Mean Squared Error (RMSE): 0.081294
R^2 (coefficient of determination): 0.9897
Although the approximation provides a good result, it has some limitations as previously described in section 2.

4.3 Data Preprocessing

The collected data allows the utilization of joint positions, torques, velocities, and currents of all seven joints as input features. The selection of the input values for the training can be adjusted as needed, varying from 7 to a total of 28 inputs (Fig. 2). However, the best result was observed with only the torques as input features for both the Feedforward and the LSTM model, see Fig.X?. The temperature values of the seven joints are used as targets. To evaluate the temperature predictions from the neural networks, randomly selected temperature measurements serve as ground truth.

4.4 Feedforward and LSTM neural networks, move this section anywhere

Table 1 compares the proposed neural networks in this paper.

Table 1. Comparison of Feedforward and LSTM neural networks

Feature	FNN	LSTM
Handles Sequential Data	No	Yes
Computational Complexity	Low	High
Training Time	Fast	Slow
Memory Requirements	Low	High
Suitable for Static Inputs	Yes	No
Suitable for Time-Series Data	No	Yes

- FNNs disregard historical information and consider each input independently. While LSTM networks are able to store the context of previous points in time (sequential data) through memory cells and use this information for future predictions (Liu et al. (2019)).
- The structure of FNNs is simple and can be trained with lower computational power and in a shorter time compared to LSTMs, which consists of more complex structures (gates). LSTMs store and update past information.
- Joint temperatures change due to continous load, movement and position. This can be detected by LSTMs, since they were specifically desinged for time series. FNNs are more suitable for regression problems on static data points, similar to the approximation of the temperature curve (see Fig. 3)

Table 2. Margin settings

Page	Top	Bottom	Left/Right
First	3.5	2.5	1.5
Rest	2.5	2.5	1.5

4.5 Figures

5. PROPOSED MODELS (VARIOUS LSTMS, FEEDFORWARD) [AND EVALUATION?]

- various LSTMs (Strcuture: Hyperparameter Learning Rate, Epochs, Batch Size, no. of Layers, Regularization, adam optimization, RMSE, True vs Predicted Temps, etc.)
- Feedforward (same as above)
- fitted function?
- Evaluations

6. APPLICATION

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7. DISCUSSION?

?

8. CONCLUSION

A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

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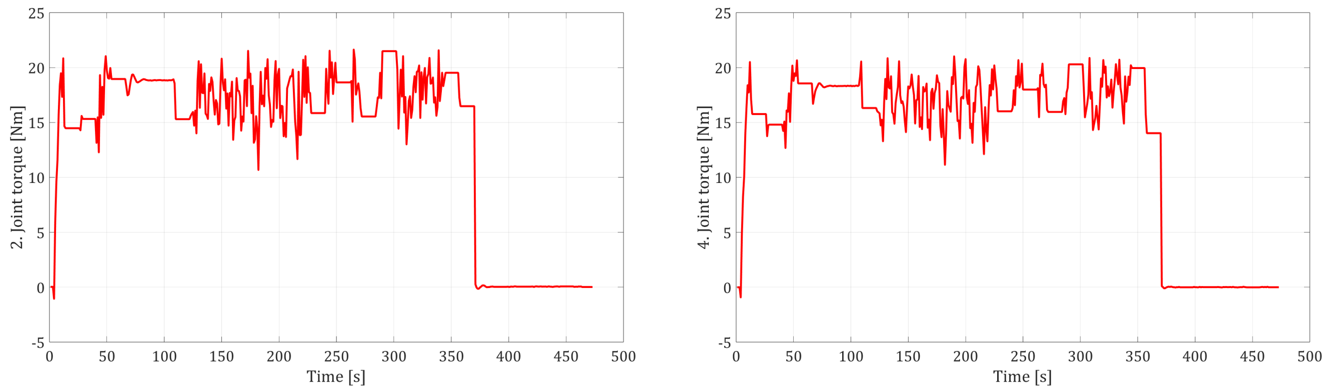
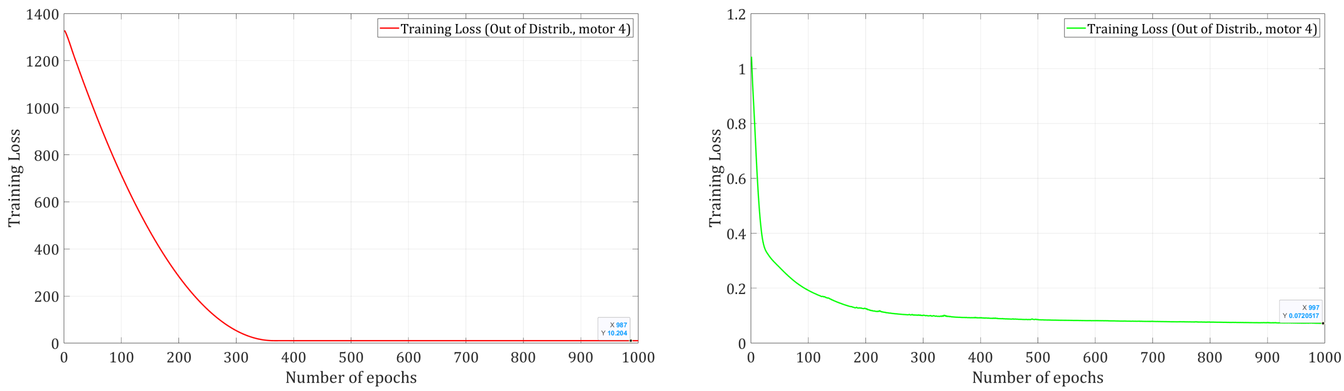


(a) Torque profile of the 2. motor.

(b) Torque profile of the 4. motor.

Fig. 4. Two different non-trivial torque profiles of the robot in Fig. 1. Observe that the profiles go beyond step functions.



(a) Training loss without data normalization.

(b) Training loss with z-score data normalization.

Fig. 5. Enhanced convergence velocity and effectiveness of the training loss through data normalization.

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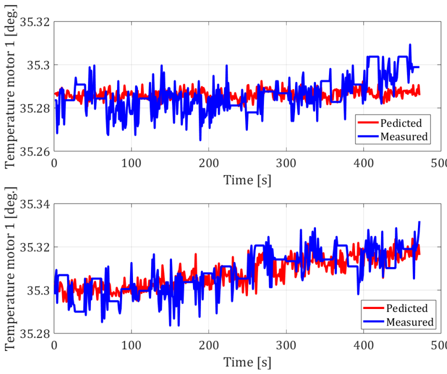
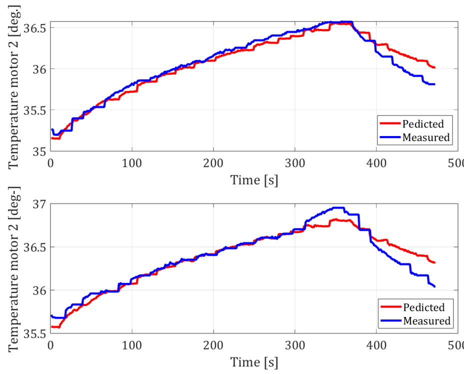
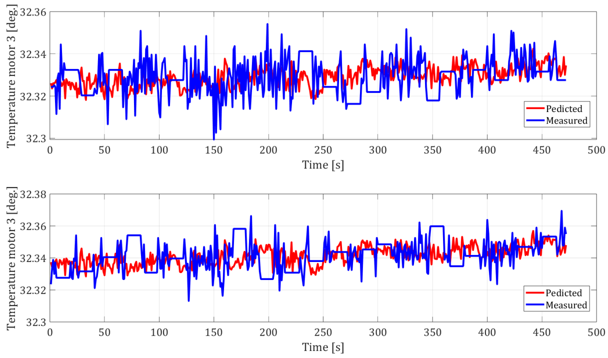


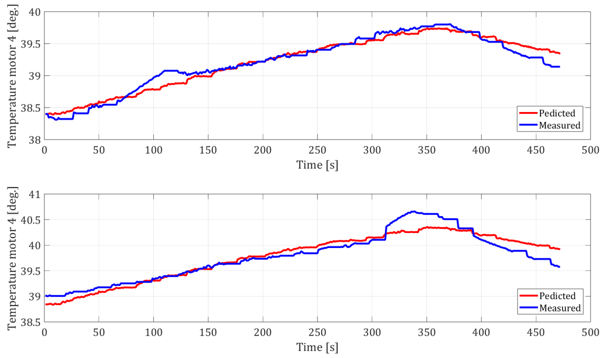
(a) Motor 1: Different predictions with **unseen** joint torques.



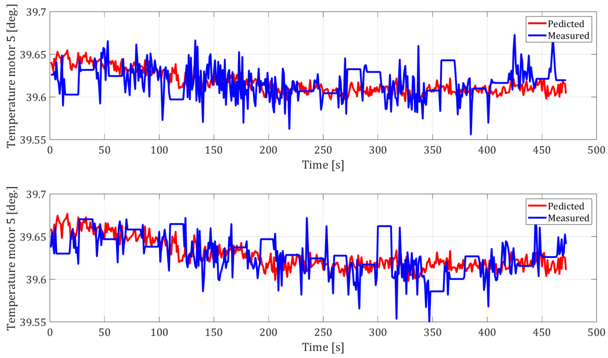
(b) Motor 2: Different predictions with **unseen** joint torques.



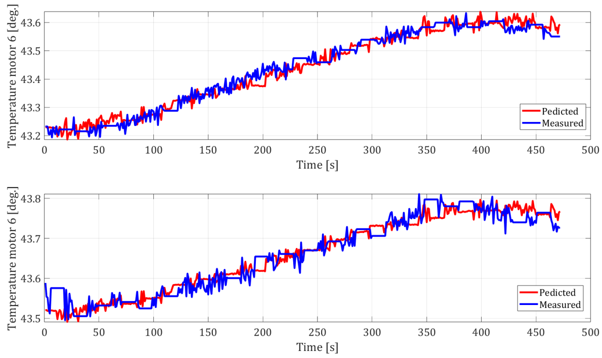
(c) Motor 3: Different predictions with **unseen** joint torques.



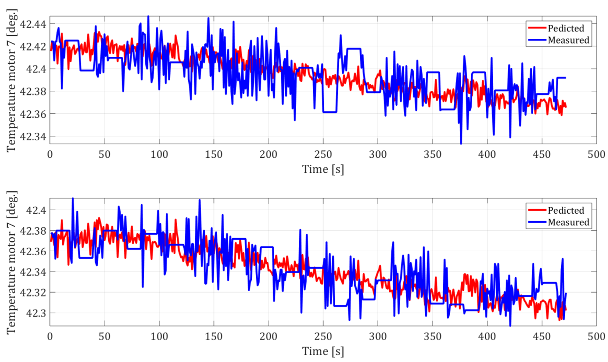
(d) Motor 4: Different predictions with **unseen** joint torques.



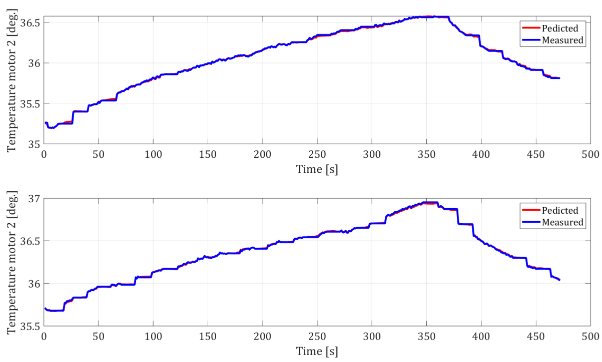
(e) Motor 5: Different predictions with **unseen** joint torques.



(f) Motor 6: Different predictions with **unseen** joint torques.



(g) Motor 7: Different predictions with **unseen** joint torques.



(h) Motor 2: Different predictions with **seen** joint torques.

Fig. 6. Capturing the thermal behavior of joint motors of the robot in Fig. 1 with previously unseen and seen data.

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Appendix A. A SUMMARY OF LATIN GRAMMAR

Appendix B. SOME LATIN VOCABULARY